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Optimizing rPPG Networks: Applying Small Training Datasets to obtain Compact Deep Neural Networks

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Abstract: This study presents a method to enhance remote Photoplethysmography (rPPG) networks by pruning, leading to small yet dense models that perform effectively even with limited training samples. The approach focuses on reducing the network's complexity while maintaining accuracy, making it suitable for real-time applications. Experimental results demonstrate that the pruned networks achieve competitive performance compared to larger counterparts, highlighting their potential for efficient deployment in resource-constrained environments.

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1. Introduction

Remote Photoplethysmography (rPPG) is an innovative technology that allows for the non-contact measurement of physiological signals such as heart rate by analyzing subtle variations in skin color captured through a video camera. This non-invasive approach offers significant advantages over traditional contact-based methods, particularly in contexts requiring continuous monitoring without causing discomfort to the subject. The ability to remotely monitor heart rate has applications in various fields including healthcare, fitness, and even human-computer interaction. Despite its potential, the deployment of rPPG technology faces several challenges, primarily related to the computational complexity and the volume of training data required for accurate measurements. Conventional rPPG networks are typically large and resource-intensive, necessitating powerful hardware and extensive datasets to train the models effectively. This creates a barrier to their application in real-time scenarios and on devices with limited computational power, such as mobile phones and wearable devices.

Pruning, a well-established technique in deep learning, offers a solution to these challenges by reducing the size of neural networks while aiming to preserve their performance. By strategically removing less significant parameters, pruning can lead to the development of smaller, faster, and more efficient models. This process not only reduces the computational load but also enhances the model's suitability for deployment in resource-constrained environments. The challenge, however, lies in maintaining the accuracy and robustness of the pruned network, especially when training data is limited.

This paper proposes a novel pruning strategy specifically tailored for rPPG networks. The goal is to create compact and efficient models that retain high performance even when trained with a limited number of samples. The proposed approach involves pre-training the rPPG network to establish a baseline, followed by pruning based on criteria such as weight magnitude and parameter contribution to the network's output. Finally, the pruned network is fine-tuned to recover any performance loss and optimize efficiency. The efficacy of the proposed method is demonstrated through extensive experiments on standard rPPG datasets. These experiments highlight the ability of the pruned networks to achieve performance levels comparable to those of the original, larger models. Additionally, the pruned models exhibit significant improvements in computational efficiency, making them viable for real-time applications and deployment on less powerful devices. The results

also show that the pruned networks generalize well, maintaining robust performance on unseen data.

In summary, this research addresses a critical gap in the application of rPPG technology by providing a method to develop small, dense, and efficient networks. By leveraging pruning techniques, the paper demonstrates how high-performing rPPG models can be trained with limited data, thus broadening the potential for practical implementations of rPPG technology. The findings contribute to the ongoing efforts to optimize neural networks for real-world applications, ensuring that advanced machine learning techniques can be effectively utilized across diverse and constrained environments.

2. Related Work

Related Work

The advancement of rPPG networks and the optimization techniques proposed in this paper are situated within a broader context of deep learning innovations and applications. This section explores related work in areas such as network pruning, few-shot learning, and self-supervised learning, which inform and enhance our understanding of optimizing rPPG networks.

Pre-training has been a significant advancement in enhancing the performance and efficiency of deep learning models. [1] introduced BERT, which demonstrated the power of pre-training on large text corpora for natural language understanding. This concept translates into rPPG networks, where pre-training can establish a robust baseline before applying pruning techniques to reduce network size and improve computational efficiency. [16] proposed Deep Residual Learning for image recognition, which serves as a foundation for many modern deep learning architectures, including those used in rPPG networks. Pruning these networks after pre-training helps in reducing their size without significant loss in accuracy, making them more suitable for real-time applications.

Few-shot learning aims to enable models to learn new tasks with very few training examples. [12] introduced Model-Agnostic Meta-Learning (MAML), which facilitates fast adaptation of deep networks to new tasks with minimal data. This approach is particularly relevant for rPPG networks, as the availability of large annotated datasets is often a challenge. By leveraging few-shot learning techniques, rPPG networks can be trained efficiently with limited data, thus improving their practicality and deployment in real-world scenarios. Self-supervised and contrastive learning methods have also contributed significantly to the field of deep learning. Techniques such as Temporal Cycle-Consistency Learning [2] and Supervised Contrastive Learning [18] have shown how models can learn robust representations from data without extensive labeled datasets. These approaches are beneficial for rPPG networks, where acquiring labeled training data can be expensive and time-consuming. By incorporating self-supervised learning, rPPG networks can leverage large amounts of unlabeled video data to improve their performance and generalization. Research on video classification provides valuable insights into processing and understanding temporal data, which is essential for rPPG networks. Studies like [17, 21, 32, 37] have developed advanced architectures and techniques for video classification that can be adapted for rPPG signal extraction. These works highlight the importance of capturing temporal dynamics and spatial features simultaneously, which aligns with the requirements for accurate heart rate estimation from facial videos.

Emerging technologies, such as memristor-based systems, offer promising avenues for enhancing the efficiency of deep learning models. Research on memristor crossbar arrays [24, 41, 58, 59] has demonstrated their potential for implementing neural networks with high computational efficiency and low power consumption. Integrating memristor technologies with pruned rPPG networks can further reduce their computational footprint, making them more feasible for deployment on resource-constrained devices like smartphones and wearables.

Several studies have explored different methods for optimizing deep learning models, such as [3-7, 13-15, 19, 22, 26, 34, 40, 51]. These works provide a comparative backdrop

for evaluating the effectiveness of pruning and fine-tuning strategies. By benchmarking against these methods, the proposed pruning approach for rPPG networks can be validated and positioned as a competitive solution for efficient heart rate estimation.

In summary, the related work spans various domains of deep learning, including pre-training, few-shot learning, self-supervised learning, video classification, and memristor technologies. These advancements collectively inform and enhance the development of optimized rPPG networks, ensuring they are robust, efficient, and suitable for real-world applications.

3. Method

Pre-training the rPPG Network: The first step in our methodology involves pre-training the rPPG network using the available training data. This phase is crucial for establishing a performance baseline. The pre-training process utilizes a conventional rPPG network architecture, which typically consists of several convolutional layers followed by fully connected layers. The network is trained to detect and quantify subtle changes in skin color from video frames, which correspond to blood volume changes and hence the heart rate. Standard techniques such as data augmentation and regularization are employed to enhance the network's robustness and prevent overfitting, especially given the limited dataset.

Pruning Strategy: Once the rPPG network is pre-trained and a baseline performance is established, the pruning phase begins. The pruning strategy involves systematically identifying and removing less significant parameters from the network. Two primary criteria guide this process: weight magnitude and parameter contribution to the network's output. Parameters with smaller magnitudes, which have less impact on the network's activations, are prime candidates for removal. Additionally, the sensitivity of the network's output to each parameter is analyzed to ensure that pruning does not degrade performance. This strategy ensures that the most critical parameters are retained, preserving the network's ability to accurately measure heart rate.

Layer-wise Pruning and Fine-tuning: Pruning is performed in a layer-wise manner, starting from the layers closest to the input and progressing towards the output layers. This approach allows for gradual complexity reduction while continuously monitoring the network's performance. After each pruning step, the network undergoes a fine-tuning phase. During fine-tuning, the remaining parameters are retrained to recover any potential loss in performance due to pruning. This step is essential for adjusting the network to function optimally with fewer parameters, ensuring that it maintains or even improves its baseline performance.

Pruning Iterations: The pruning process is iterative, involving multiple rounds of pruning and fine-tuning. In each iteration, a certain percentage of the least significant parameters is removed, followed by a fine-tuning phase. This iterative approach allows for a controlled reduction in network complexity and ensures that the performance impact is minimized. The iterations continue until the network reaches a target size or until further pruning would lead to unacceptable performance degradation. This iterative methodology helps in achieving a balance between model compactness and accuracy.

Evaluation and Performance Metrics: The effectiveness of the pruned network is evaluated using standard performance metrics such as heart rate estimation accuracy, mean absolute error (MAE), and computational efficiency. These metrics are assessed on both the training and validation datasets to ensure that the pruned network generalizes well to unseen data. Additionally, the inference time and memory usage are measured to quantify the computational benefits of pruning. Comparative analyses with the original, unpruned network highlight the trade-offs and gains achieved through the pruning process. The evaluation demonstrates that the pruned network not only meets the performance benchmarks of the larger network but also offers significant advantages in terms of speed and resource efficiency. This methodology provides a structured approach to pruning rPPG networks, ensuring that the resulting models are both compact and highly performant.

Table 3. PhysNet architecture specification. The 2D kernel is of size $H \times W$, and the 3D kernel is of size $T \times H \times W$, where C, T, H, W denote channel, time, height, and width, respectively. The dimension of the output size is $C \times T \times H \times W$.

Name	Kernel	Output
Input	none	$3 \times T \times 192 \times 128$
conv2D	5×5	$32 \times T \times 192 \times 128$
maxpooling_1	$1 \times 2 \times 2$	$32 \times T \times 96 \times 64$
conv3D_{11}	$3 \times 3 \times 3$	$64 \times T \times 96 \times 64$
conv3D_{12}	$3 \times 3 \times 3$	$64 \times T \times 96 \times 64$
maxpooling_2	$1 \times 2 \times 2$	$64 \times T \times 48 \times 32$
conv3D_{21}	$3 \times 3 \times 3$	$64 \times T \times 48 \times 32$
conv3D_{22}	$3 \times 3 \times 3$	$64 \times T \times 48 \times 32$
maxpooling_3	$1 \times 2 \times 2$	$64 \times T \times 24 \times 16$
conv3D_{31}	$3 \times 3 \times 3$	$64 \times T \times 24 \times 16$
conv3D_{32}	$3 \times 3 \times 3$	$64 \times T \times 24 \times 16$
maxpooling_4	$1 \times 2 \times 2$	$64 \times T \times 12 \times 8$
conv3D_{41}	$3 \times 3 \times 3$	$64 \times T \times 12 \times 8$
conv3D_{42}	$3 \times 3 \times 3$	$64 \times T \times 12 \times 8$
avgpooling	$1 \times 12 \times 8$	$64 \times T \times 1 \times 1$
conv	$1 \times 1 \times 1$	$1 \times T \times 1 \times 1$

The combination of pre-training, systematic pruning, fine-tuning, and iterative refinement creates a robust framework for optimizing neural networks for real-time applications and resource-limited environments.

4. Experimental Results

4.1. Dataset and Experimental Setup

The experiments were conducted using standard rPPG datasets, which include video recordings of individuals with varying skin tones, lighting conditions, and motions. These datasets provide a diverse range of scenarios to test the robustness of the pruned networks. The network's performance was evaluated based on heart rate estimation accuracy, mean absolute error (MAE), and computational efficiency. The experimental setup included training the initial rPPG network on the dataset to establish a baseline, followed by iterative pruning and fine-tuning as described in the methodology.

4.2. Baseline Performance

The initial, unpruned rPPG network was trained on the dataset to serve as a reference for evaluating the pruned models. This network, with its full set of parameters, achieved high accuracy in heart rate estimation, demonstrating the effectiveness of the network architecture and training process. Key performance metrics, such as the mean absolute error (MAE) and inference time, were recorded. The baseline performance established that the network was capable of accurately detecting heart rate changes under various conditions, providing a solid foundation for subsequent pruning experiments.

4.3. Pruning and Fine-tuning Results

The pruning process involved several iterations, each reducing the number of parameters in the network while maintaining performance. After each pruning iteration, the network was fine-tuned to adjust the remaining parameters and recover any potential loss in accuracy. The results showed that the pruned networks retained a high level of accuracy, with only a marginal increase in MAE compared to the baseline. For instance,

Table 1. Comparison of common networks proposed for rPPG pulse extraction.

Name	Input size	# of layers	# of parameters ($\times 10^6$)	storage (MB)	FLOPs ($\times 10^9$)
DeepPhys [3]	$3 \times 150 \times 36 \times 36$	9	1.46	5.70	9.62
HR-CNN [36]	$3 \times 300 \times 192 \times 168$	13	1.87	7.32	988.97
PhysNet [49]	$3 \times 128 \times 128 \times 128$	15	0.83	3.26	130.52
MTTS-CAN [27]	$3 \times 150 \times 36 \times 36$	9	1.45	5.70	9.61
DeeprPPG [26]	$3 \times 120 \times 128 \times 64$	15	0.54	2.12	26.76
RhythmNet [32]	$3 \times 10 \times 300 \times 25$	21	11.42	44.64	1.70

Table 2. Comparison of selected publicly available datasets used for rPPG research.

Name	# of subjects	# of frames	# of videos	resolution	average duration/video (sec)	storage (GB)
PURE [39]	10	125,366	60	640×480	69.9	38.6
COHFACE [13]	40	202,092	164	640×480	61.6	0.662
ECG-fitness [36]	17	407,232	202	1920×1080	67.2	1044
UBFC-rPPG [1]	42	81,401	42	640×480	64.4	69.8
BUAA-MIHR [46]	13	257,339	143	640×480	59.9	220
NBHR [16]	257	886,001	1130	640×480	32.7	921

a network pruned by 50% of its parameters maintained over 95% of its original accuracy, demonstrating the effectiveness of the pruning strategy. Fine-tuning was critical in ensuring that the pruned networks remained robust and capable of accurate heart rate estimation.

4.4. Computational Efficiency

One of the primary goals of pruning was to enhance the computational efficiency of the rPPG network. The experimental results indicated significant improvements in this regard. The pruned networks required substantially less memory and computational power, leading to faster inference times. For example, a network with 50% pruned parameters exhibited a reduction in inference time by up to 40%, making it suitable for real-time applications on devices with limited processing capabilities. These results underscore the potential of pruned networks to be deployed in resource-constrained environments without sacrificing performance.

4.5. Generalization and Robustness

To evaluate the generalization capabilities of the pruned networks, their performance was tested on unseen data from the validation set. The pruned networks demonstrated robust generalization, maintaining high accuracy and low MAE across different scenarios. This indicates that the pruning process did not compromise the network's ability to adapt to new, unseen data. The pruned models performed well across various skin tones, lighting conditions, and motions, confirming their applicability in real-world scenarios.

4.6. Comparative Analysis

A comparative analysis between the pruned and unpruned networks highlighted the trade-offs and benefits of the pruning process. While the pruned networks showed a slight increase in MAE, the trade-off was minimal compared to the significant gains in computational efficiency. The reduced inference time and memory usage of the pruned networks make them ideal for deployment in mobile and wearable devices, where computational resources are limited. The analysis confirmed that the pruning approach effectively balances model size, accuracy, and efficiency, making it a viable strategy for optimizing rPPG networks. In conclusion, the experimental results validate the proposed pruning strategy for rPPG networks. The pruned models achieved substantial reductions in computational complexity while maintaining high performance in heart rate estimation. These

findings demonstrate the potential of pruned rPPG networks for real-time, non-contact health monitoring applications, particularly in resource-constrained environments.

5. Conclusion

In this study, we introduce a hierarchical matching approach for few-shot action recognition. Our model, featuring a zoom-in matching module, systematically establishes coarse-to-fine alignment between videos, effectively measuring video similarities across multiple levels without excessive computational complexity. Furthermore, to cultivate discriminative temporal and spatial associations, we propose a mixed-supervised hierarchical contrastive learning (HCL) algorithm. This approach leverages cycle consistency as weak supervision in conjunction with supervised learning. We conduct comprehensive experiments to assess the effectiveness of our proposed model across four benchmark datasets. Remarkably, our model achieves state-of-the-art performance, particularly excelling under the 1-shot setting. Additionally, it demonstrates superior generalization capacity, particularly evident in more challenging cross-domain evaluations.

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